Using Artificial Neural Networks to Calculate Lift Coefficients for an Unknown Airfoil

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The process for calculating the lift coefficients for an unknown airfoil today is still based on a practice discovered in 1929 where Langley had perfected their design of the NACA airfoils system. This is a catalog composed of 78 airfoils that appeared for the first time in NACA's annual report in 1933. When it comes to developing a new airfoil, engineers have tried to modernize the trial-and-error method by using Computational Fluid Dynamics (CFD) models, but this process has its limits. Using CFD models, engineers are able to see an approximate representation of flow over an airfoil. However, CFD models are used in the beginning phases of development, where assumptions concerning the flow type can be idealized. This means as engineers move out of the beginning stages and toward the developmental stages, the CFD model becomes only an introduction to the process. With the rise of AI and deep machine learning, the potential usefulness of an artificial neural network (ANN) takes root. The use of ANNs could prove to be revolutionary in developing unknown airfoils because of their ability to learn. ANNs can be trained on known data, such as equations to represent the shape of known airfoils and their known lift coefficients, and then would be tested on their ability to produce accurate coefficients given only the shape of the airfoil. This paper will discuss the history of airfoils, how to potentially implement ANNs in the process of developing new airfoils, and how this will propel us into the future.

I. Background

This paper attempts to simplify how and why simulating an airfoil using artificial intelligence is beneficial and sustainable. The authors of this paper followed the research of many other similar papers and, in maintaining simplicity, will only focus on the process of calculating the coefficient of lift using artificial neural networks. This section will cover all the historical context needed to follow through the rest of the paper easily.

In 1903, the Wright brothers completed their first successful aircraft flight, and the innovations for flight took off, with Robert Goddard already experimenting with rocketry in 1914. Falling behind to countries like Europe, which had already established and begun progress in its own flight developments, the United States quickly recognized the need for America as a country to make a mark in this revolutionary period, and so the National Advisory Committee for Aeronautics (NACA) was born. The NACA was established in 1915, and its main goal was 'to supervise and direct the scientific study of the problems of flight, with a view to their practical solutions'[6]. Named after the Smithsonian Samuel Langley, the NACA's first laboratory became a hotspot for aspiring engineers. At Langley, cutting-edge research took place, and in 1920, the Langley wind tunnel, as seen in Figure 1, took the stage. By 1921, engineers at Langley were using models in the wind tunnel and testing models in their Variable Density Tunnel. By conducting scaled tests here, engineers were able to make accurate measurements and assumptions into scaled-up models using something called a Reynolds Number. In 1922, Langley was recognized as the 'primary source for aerodynamic data at high Reynolds Numbers in the United States, if not in the world'[6]. With rapid research and developments continuing, by 1929, Langley had developed a detailed catalog system of 78 airfoils, which was published in 1933. In 1958, NACA officially became the National Aeronautics and Space Administration (NASA). It was the end of an era as far as nomenclature, but the goals and flight developments continued and began to include space in flight research.

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Figure 1: Langley's First Wind-Tunnel built in 1920 [6]

Though today's wind tunnels are larger and have higher windspeed capabilities, this system of developing airfoils via testing and scaling Reynolds numbers would continue with little to no improvements until the late 1980s when a system known as Computational Fluid Dynamics (CFD) modeling, as seen in Figure 2, was introduced into the field. [18] In a general sense, CFD models simulate flow over a defined surface, which is helpful for demonstrating how an airfoil might perform under specified conditions. Using CFD models, engineers are able to gain an early visual and determine how to troubleshoot an issue when the simulation doesn't run as hypothesized. Since airfoils are 2D cross sections of a 3D wing, CFD is essential for visualization of what the airfoil will look like as air flows over a wing. Though CFD models are helpful tools for visualization, they don't help solve specific questions of flight. This includes the question of this paper: how to calculate the coefficient of lift without wind tunnel testing. This is because their modeling system is based on the Navier-Stokes theory [19], and this theory makes several assumptions that, unfortunately, don't translate to real-world flight.

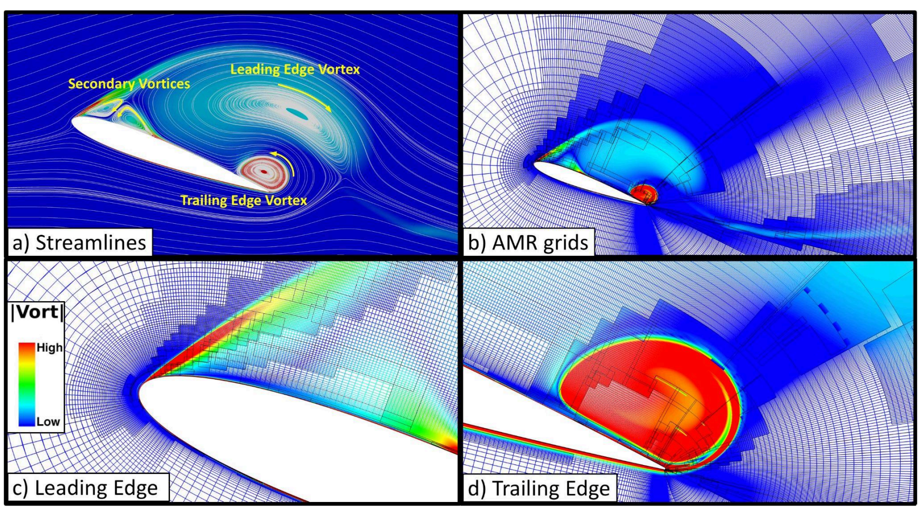

Figure 2: What Does a CFD Model Look Like? [22]

The Navier-Stokes theory is challenging to use mathematically when solving for lift calculations, so assumptions such as inviscid flow (flow with zero viscosity) are made to simplify it. This leads to a model that doesn't fully demonstrate lift under genuine atmospheric conditions [1]. This is why airfoil testing in wind tunnels and variable density tunnels are still crucial parts of determining the mathematical demonstration of an airfoil. For example, calculations such as the lift force are found using a force balance, and forces such as dynamic pressure are found using pressure sensors during wind tunnel experimentation [20]. Figure 3 demonstrates this. The coefficients at different angles of attack are then found using the calculations from the wind tunnel. Though these calculations may be coupled with CFD models, these models are never really exclusively used or relied on entirely. Furthermore, CFD models are helpful for observations and provide limited data in terms of mathematical calculations. Hence, wind tunnel testing is where most of the data comes from, but since the NASA CFD 2030 initiative was launched in 2014, there has been increased research toward developing CFD in the aerospace field. This is where artificial neural networks (ANNs) could be introduced. In subsequent sections, this paper will suggest a blueprinted idea of an ANN and how beneficial this tool would be to the aerospace field and accomplishing NASA's CFD 2030 goals.

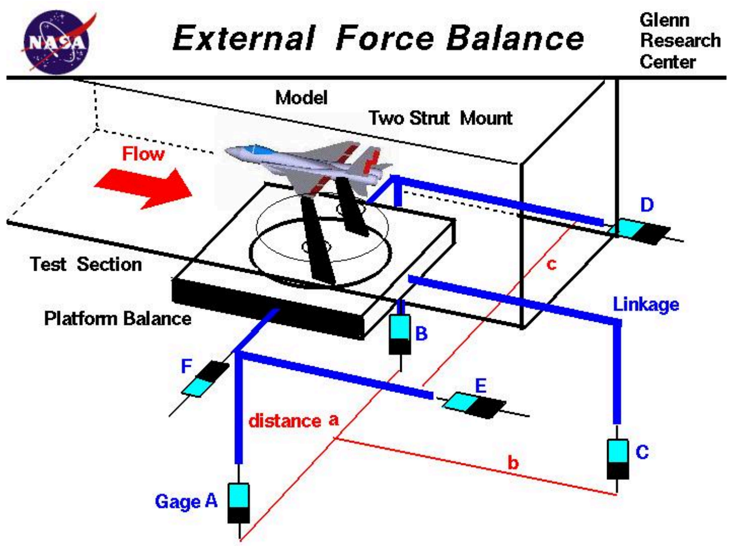

Figure 3: Visual of External Force Balance During Wind Tunnel Testing [21]

II. Airfoil Basics

Given the background of what goes into developing a successful airfoil and finding the accurate coefficients of the airfoil at different points, it is important to cover the parts of an airfoil in order to understand the input information of the artificial neural network. This section will focus on what an airfoil is, how this is relevant to the coefficient of lift, and the relationship an airfoil will have with the proposed neural network.

To answer the question: what does an airfoil look like, refer to Figure 2. An airfoil can take several different shapes, but most have a teardrop resemblance with a rounded front and a pointed end. An airfoil is simply a 2D cross-section of a 3D wing. It is used to optimize the relationship between lift and drag at different moments during flight. An airfoil has several different components: leading edge, trailing edge, chord line, camber, mean camber line, thickness, shape, angle of attack, Lift force, Drag force, and moment. Figure 4 illustrates each of these components in relation to the airfoil. Each of these elements has different effects on the airfoil's performance. Via the coefficients determined during wind tunnel testing, the airfoil, in turn, relates to the performance of the entire aircraft [13].

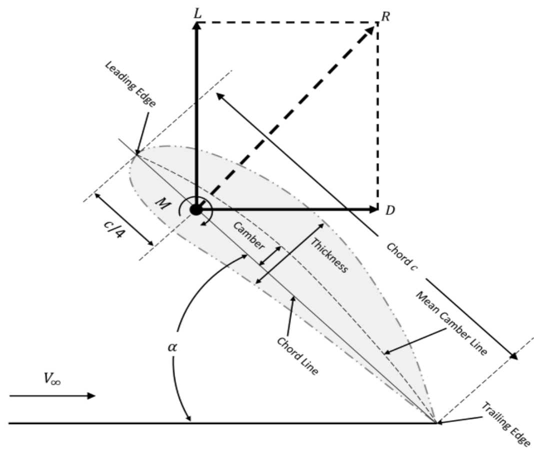

Figure 4: Labeled Diagram of Airfoil Components [13]

The first component is the leading edge, this is simply the forwardmost point of the airfoil. The chord line and the mean camber line both stem from this point. The next component is the trailing edge. This is opposite the leading edge and, therefore, the rearmost point of the airfoil. The chord line and mean camber line connect again at the trailing edge. The camber is the maximum distance between the mean camber line and the chord line. The mean camber line goes from the leading edge to the trailing edge and evenly splits the airfoil, making a curved shape. The thickness is the vertical length of the airfoil measured at the greatest point. The shape of conventional airfoils resembles a teardrop shape, although not all airfoils do, for reference, see Figure 5, which illustrates a non-conventional airfoil. The angle of attack is the incline angle between the horizontal and the airfoil. The Lift force is the force acting in the upward direction and is perpendicular to the Drag force. The Drag force is the horizontal force that acts opposite of forward movement. The moment is the force that causes the airfoil to want to rotate about the aerodynamic center.

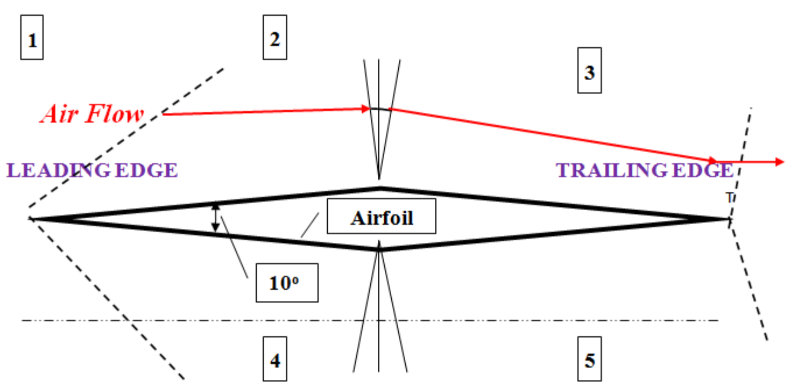

Figure 5: Non-conventional, Wedge Airfoil for Supersonic Flight [23]

All the airfoil elements are used to evaluate performance, but more important to the research of this paper, the lift force is used to find the coefficient of lift. Taking the data from known airfoils, it is relatively simple to find the coefficient of lift via an equation or a lift coefficient (C_L) vs. angle of attack plot, as seen in Figure 6, but what if the airfoil is unknown? How can the coefficient of lift be found without going through the tedious and time-consuming testing with wind tunnels and current CFD models?

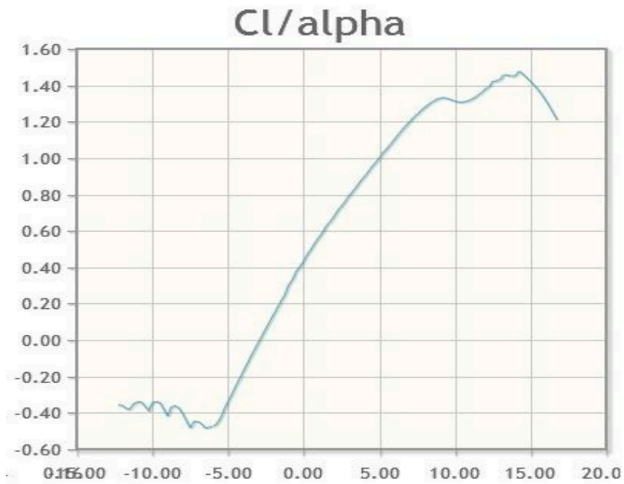

Figure 6: C_L vs Alpha Plot [24]

III. Engineering Aspects

This section will evaluate the above predicament and produce a possible solution using an artificial neural network. It is divided into two sub-parts. The first section will discuss the lift coefficient and its analytical definition. The second section will introduce artificial neural networks and provide a relevant example of research, including ANNs.

A. Lift Coefficient (C_L)

The lift force depends on wing surface area, true airspeed, pressure, temperature, altitude, humidity, dynamic pressure, and the lift coefficient. As previously explained, these components are found during wind tunnel testing, and from there, the lift coefficient at varying angles of attack can be found. The lift coefficient is a unitless number, so when switched from a 2D airfoil to a 3D wing, the lift coefficient will remain the same. C_L is just one piece of the flight puzzle, but to demonstrate the potential of artificial neural networks, the C_L will be treated as the most significant piece.

B. Artificial Neural Networks

Artificial neural networks and their potential are a large focus of this paper. To answer the question of what an ANN is and how it is relevant, consider the similar question of why functions are relevant. It is commonly known that functions are the universal language of the world. Everything can be communicated and illustrated via functions so long as the function can be defined. This is where ANNs gain their relevance. An artificial neural network can be considered a universal function approximator [25]. "The universal approximation theorem states that a neural network with at least one hidden layer … can approximate any continuous function to an arbitrary level of accuracy" [26].

In other words, neural networks can model complex relationships between inputs and outputs of a function without explicitly knowing the functions. The components of a neural network mimic a brain. Different neurons process different amounts of data and produce an output based on what the neurons identify. Each neuron can take any number of inputs and will produce one output. Each output is then viewed as the input to another set of neurons, and the process continues until the network outputs the desired data. The process of the neurons processing data is known as the hidden layer; the hidden layer also accounts for errors and bias and uses the backpropagation method to reduce this. Before a neural network can produce usable data, it has to be taught. The network's ability to learn is what truly makes ANNs so beneficial. Figure 7 provides a conceptual model of a neural network and its layers. The green represents input nodes, the blue is the hidden layer, and the red is the output. Each arrow pointing to a different node can be thought of as a neuron.

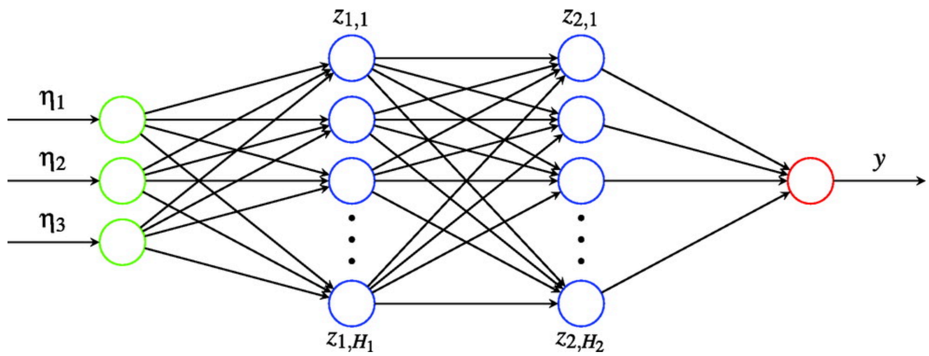

Figure 7: Map of Neural Network

Thus, neural networks are made to solve functions with difficult parameters, such as the Lift equation, where the data can only be found experimentally. By taking the known experimental data, the neural network aims to approximate its own function and predict the C_L to a desired degree of accuracy, and the greater the training set, the greater the accuracy. Though the authors of this paper did not develop their own network, thorough research and evaluation of other networks relating to this concept were done. The best network found to illustrate the ideas of this paper comes from source 13.

First, a problem statement needs to be identified to build a network: how to predict the coefficient of lift of an airfoil where all other mathematical data is unknown and given only its shape. Then, an activation function needs to be selected; the most common of these is the rectified linear unit function (ReLU), and conveniently, the neural network evaluated in this paper used the ReLU function. The next step requires a more complex understanding of linear algebra and coding, which is outside the scope of this paper. Finally, the ANN simply needs to be taught. By feeding it the known inputs of shape and size and other measurable features without wind tunnel testing and known outputs of C_Ls that vary with the angle of attack, the ANN should be able to predict an accurate lift coefficient at the desired angle of attack. Figure 8 shows the accuracy of the ANN from source 13, which is clearly very accurate. Though the ANN struggles with identifying an accurate coefficient at the stall moments, this would ideally be troubleshot during the test phases.

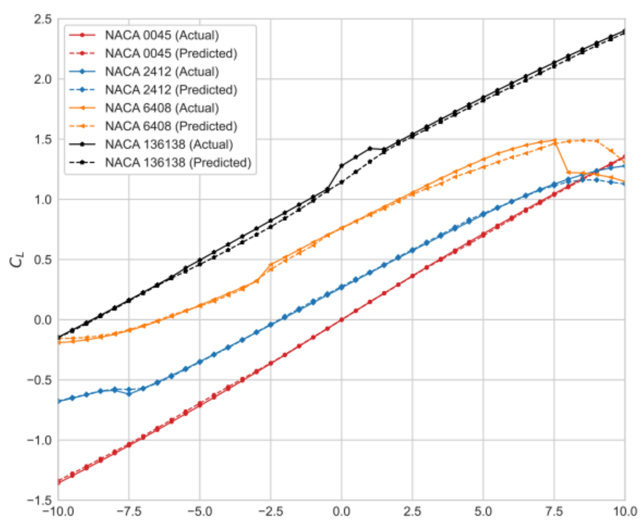

Figure 8: Comparison of Neural Network Predictions to Actual Calculations [13]

IV. Computational Fluid Dynamics 2030

This section will briefly outline how to begin implementing the neural network in the current process and how to eventually fully transition to relying on neural networks. The NASA CFD 2030 goals have outlined a desire to 'develop and demonstrate computationally efficient… tools that predict maximum lift for transport aircraft with the same accuracy as certification flight tests' [7]. The use of neural networks is the key to accomplishing this. Suppose neural networks were implemented by the end of 2024 and used to calculate the Lift and Drag force and their coefficients. By 2030, it is predicted that millions of dollars that would have previously gone toward physical airfoil testing could be saved [7], not to mention how much time engineers could redirect towards other tasks overall improving efficiency. This paper has narrowed its research scope by focusing only on the lift coefficient, but the ideas outlined could easily be applied to other relevant coefficients. Following the development of a successful neural network, the next steps are to evaluate how this new machine-learning technique would benefit the aerospace field.

As stated in the above section, the more data used to train a neural network, the better it will predict the outputs. Thus, continually training the network and slowly transitioning to fully using it is the best option. Initially, the neural network should be used simultaneously with wind tunnel testing to work through its hiccups, like the issue of predicting an accurate stall coefficient, as seen in Figure 8. Depending on the initial quality of the neural network, this training may take years to perfect, but the patience is worth it. Until the network can accurately predict the C_L, users must continue checking and testing throughout the pilot stage. Once the network is deemed reliable and the error found through rigorous testing is negligible, users may exit the pilot stage and begin to rely on the neural network. Ideally, this would only require a developed airfoil to go through wind tunnel testing in its final stages. Implementing ANNs into the development of airfoils allows airfoils to be designed faster, cheaper, and at the same quality as before. Overall, choosing to depend on neural networks for developing airfoils is easy.

V.Conclusion

This paper has covered what it would look like to use artificial neural networks to calculate the lift coefficient for an unknown airfoil. While the authors of this paper did not develop their own neural network, a comprehensive review of similar research is equally useful in illustrating the goals of the paper. Simulating an airfoil is both sustainable and beneficial simply because of the time and resources it saves. It enables engineers to develop and finalize projects significantly faster, keeping the same quality.

The United States has historically fallen behind other countries when groundbreaking aerospace technologies have been discovered. If the narrative is ever going to change, it is important to look to machine learning. Artificial neural networks are clearly an easy choice because of their learning ability, which leads to increased accuracy over time.

Following the process of developing and implementing a neural network centered around the lift coefficient makes it easier to expand this scope and apply neural networks to other aspects of airfoil development. Finally, the paper's overall conclusion is as follows: artificial neural networks can predict the lift coefficient of an unknown airfoil and, with time, could replace the current process, pushing NASA closer to its CFD 2030 goals.

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